A Spiking Neural Network System and Its Applications

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1. Introduction

The brain is an amazingly complex and efficient machine. While it may not be considered "general purpose" in terms of its computational capabilities, it performs a set of functions such as feature extraction, classification, synthesis, recognition, learning, and higher-order decision-making amazingly well [1]. Neuroscientists and researchers have been working hard for past many years to understand the functioning of brain which comprises of network of biological neurons. A single neuron acts as a basic computing unit and network of such neurons form one of the most complex network to understand as far as its processing capability and behavior is concerned. Brain may not be considered "general purpose" in terms of its computational capabilities, it performs a set of functions such as feature extraction, classification, synthesis, recognition, learning, and higher-order decision-making amazingly well [1]. So, it has been a challenge for brain researchers for so many years to understand the mechanism which a biological neuron uses to interpret and treat information [2], [3] . A feasible way to study the different brain capabilities is to artificially reproduce those systems by using biologically plausible neural implementations [2]. The field of Artificial Spiking Neural Networks is an attempt to emphasize the neurobiological aspects of artificial neural computation [4].Spiking Neural Network is the third generation of Artificial Neural Network which has emerged and has been making advancement in exploring the information processing capabilities of brain [5]. Spiking Neural Networks (SNNs) are believed to be biologically more plausible and computationally more powerful than analog neural networks [6]. Before going into the details of Spiking Neural Network, let us now understand where they lie in the hierarchy of neural network. Neural network can be broadly classified into two classes:

1.1 Artificial Neural Network

Biologically realistic neural networks are networks that have a closer association with what is known about the way brains process information. In these networks basic processing unit is a neuron. Neuron models are comprised of four parts for example input, trigger, conduction and output [7]. These neurons communicate with the medium of short and sudden electrical pulses called ‘spikes’ or action potentials [8].

Depending upon the computational units, neural networks can be classified in three generations ([9] [10]). *First generation networks* are based on McCulloch and Pitts’ neurons as computational units, i.e. with only digital outputs [11]. *Second generation networks* are based on computational units that apply an activation function with a continuous set of possible output values, such as sigmoid or polynomial or exponential functions. *Third generation or Spiking Neural Network*: In these networks computational units are spiking neurons which takes spike events as input, process them and generates spike events as output [10]. Next section describes Spiking Neural Network and its features in detail.

2. Spiking Neural Network

Basic computational unit in these network is spiking neuron model which takes precisely timed spike train as inputs and are capable to process them and produce precisely timed spike trains as output. For information coding these networks consider spatio-temporal spike trains. Recent advances have shown that, because of the inclusion of time domain, Spiking Neural Network (SNN) models are more efficient and capable to capture neuronal behavior more accurately than a traditional neural network [10]. In traditional neural network, neurons fire at each propagation cycle, however in SNN a spiking neuron only fires when a membrane potential reach its threshold. Spiking neural networks (SNNs) exhibit interesting properties that make them particularly suitable for applications that require fast and efficient computation and where the timing of input/output signals carries important information [12].

Application area of spiking neural networks are huge, for example these models are applicable on elementary processes in the brain, including neural information processing, plasticity, learning and formation of associative memories, simulation of brain parts such as hippocampus. As well as problems in applied engineering, e.g. fast signal-processing, event detection, classification, pattern recognition, speech recognition, spatial navigation or motor control ([13], [14], [15]), however, classical neural networks is still used to solve some of such problems, e.g. Decision Support System and Robot Path Planning [16].

In the third generation Spiking Neural Network, information transfer in the neuron models via the precise timing of spikes or a sequence of spikes. Potential to solve complicated time-dependent pattern recognition problems lies in SNNs because of their dynamic representation [10]. Networks of spiking neurons are more powerful than their non-spiking predecessors as they can encode temporal information in their signals [17]. Other areas where spiking neural networks have been used comprises of a model for the simulation of visual attention [18]. Using extraction of horizontal and vertical lines, a demonstration shows how the network can detect a house in a visual image. This was combined with edge detection network model [19]. This spiking neural network with spiking neurons are able to perform very complicated computation tasks, learning tasks and intelligent behaviors in the human brain [18]. So far experiments have been done only on an image of house but it can be used on more complex images [19].Kasabov and team has contributed a lot in the area of evolving Spiking Neural Networks (eSNN). These models have the capability to comprise and incorporate different dimensions of information like frequency, time, phase, space and to cope with heavy amounts of data in a self-organizing and adaptive manner and thus they have the potential to model composite information processes. Machine which deals extremely well with the spatio-temporal data is the brain. Brain performs as a spatio-temporal information processing machine. So idea is to evolve to a spiking neural network to explore such functionality. [20].In the domain of neuroinformatics, ecology, environment, medicine, economics, engineering, bioinformatics etc the type of data which gets collected commonly can be broadly categorized as Spatio and spectro-temporal data or SSTD. The main issue here is that there do not exist sufficient

methods for the identification of complex spatio-temporal patterns and for spatiotemporal pattern recognition (STPR). Spiking Neural Networks (SNN), being the third generation of neural networks, are a bright paradigm for the development of new intelligent ICT for spectro-temporal data. In another work in 2012, Kasabov had done a survey on the evolution of the evolving connectionist systems (ECOS) paradigm, from simple ECOS to evolving spiking neural networks (eSNN) and neurogenetic systems [21]. This paper talks about methods for spatio and spectro temporal pattern recognition.

2.1 Spiking Neuron Model:

A biological neuron has been represented by different mathematical models. For example:
Integrate & Fire Model: This model which is simple and powerful model describes the relationship between membrane potential and action potential. As soon as membrane potential hits the threshold value, spike goes out. In this model spikes do not possess latencies because of the constant threshold. If its firing properties are compared with the real neuron, it is unable to produce all the firing patterns [22].

Leaky Integrate and Fire Model: This is the more realistic version of the ideal integrate and fire neuron model. In this model the membrane leaks and as a result the cell potential has a tendency to decay back towards its resting value. In other words, input is linearly integrated and it is not dependent on the postsynaptic neuron state. Because of this mechanism of resetting membrane potential after each output spike, memory of prior spike is lost. Since it is very simple it fails in various prospects of neural dynamics [23].

I&F with Adaptation [24]: Because of its 1-D nature, this model cannot show bursting and other features of real neuron. Spike frequency adaptation phenomenon is supplied in this model because of the presence of a second linear equation which depicts dynamics of K current. As reported in [22], for 1ms time step it requires 10 floating point operations.

Integrate-and-Fire-or-Burst (I&FB) Model: This was proposed by Smith and coauthors [25] but later explained by Ezhikevich in [22]. It has 2 variables because of which this model is able to produce bursting property. Ezhikevich in [22] had performed experiments which shows that it is computationally expensive and to simulate 1ms of the model, it requires between 9 and 13 operations.

Resonate-and-Fire Model: This model was proposed by Ezhikevich [26]. It uses complex state variable. These neuron model expects input with a specific resonate frequency which is closed to its Eigen frequency. In I&F model, if the frequency of the input is high then there more chances that the neuron will fire early but in this model high frequency input can even retard or stop neuronal response. The time interval between two spikes is important in this model.

Quadratic I&F Model: As per Ezhikevich in [22], quadratic I&F neuron is an alternative to the leaky I&F neuron model. It is also known as the theta-neuron. This Quadratic model ([27] [28] [29]) is a particular illustration of a nonlinear integrate-and-fire model. As per the experiment conducted by Ezhikevich in [22], to simulate 1 ms of the model, it requires 7 operations. It can be opted if the goal is to simulate large-scale integrators network. Because of its one dimensional nature, it is unable to produce bursting properties as well as spike frequency adaptation.

Spiking Model by Izhikevich: This was proposed by Ezhikevich. It has computational power of integrate-and-fire model and properties of real neuron just like HH model. Model is dependent on 4 parameters and can produce spiking and bursting properties of some cortical neurons. As per Ezhikevich in [24], using this model, one can simulate tens of thousands of spiking cortical neurons in 1 ms resolution using a desktop PC [29].

Hodgkin–Huxley: This is one of the basic and most important model which was proposed by [30]. The membrane potential, inactivation of Na current and activation of Na and K currents were described by 4 differential equations and tens of parameters. As per Ezhikevich in [22], model takes 120 floating point operations to evaluate 0.1 ms of model time with an assumption that each exponent takes only ten operations, thus, 1200 operations per ms. It can only be used when simulation time is not an issue and requirement is to simulate very less neurons.

Spike Response Model: This was proposed by Gerstner in [31] and it is an abstraction of leaky integrate-and-fire model. In this model parameters depend on the time since the last output spike. The membrane potential at certain time instant t is expressed as an integral over the past. There is a dependency of the membrane potential upon the last output spike. The dynamics of neuron depends only on its most recent firing time.

Main limitations of existing spiking neuron models:

- Unable to produce all firing patterns which are shown by a real biological neuron
- Computationally expensive
- Takes much simulation time
- Requires large floating point operations
- Few models are not capable to store information about previous spike so no memorizing capability

As a result of review of existing neuron models, it is evident that in order to explore some aspects of information processing within the brain, there is a need to explore more computationally efficient and biologically plausible cortical spiking neurons.

3. Spikes and Information Processing

Next we will try to present the relation between spikes and information processing in a real neuron. In a mammalian brain, in every small volume of cortex, thousands of spikes are emitted each millisecond. What is the information contained in such a spatiotemporal pattern of pulses? What is the code used by the neurons to transmit that information? How might other neurons decode the signal? As external observers, can we read the code and understand the message of the neuronal activity pattern? The above questions point to the problem of neuronal coding, one of the fundamental issues in neuroscience [23]. The answer lies in the concept of neural coding schemes.

3.1 Rate Coding

Traditionally it has been thought that most, of the relevant information was contained in the mean firing rate of the neuron. The experimentalist sets a time window of, say, T = 100 ms or T = 500 ms and counts the number of spikes that occur in this time window. Division by the length of the time window gives the mean firing rate. It is reported in Hz [23].

3.2 Spike Coding

Here are some potential coding strategies based on spike timing.

Time-to-first-spike: In order to understand this term, let's take a neuron which suddenly receives an input at certain time instant *t* and fires quickly after receiving the input signal. This behavior shows that, for this particular neuron, stimulation is strong. Thus imagine a code, where for each neuron, the timing of the first spike after the reference signal, contains all information about the new stimulus. This coding scheme is known as 'time-to-first-spike'. In this scheme each neuron only needs to fire a single spike to transmit information. Only the first spike after the reference signal counts, all following spikes would be irrelevant. [23].

Phase: We can apply a code by 'time-to-first-spike' also in the situation where the reference signal is not a single event, but a periodic signal. In the hippocampus, in the olfactory system, and also in other areas of the brain, oscillations of some global variable (for example the population activity) are quite common. These oscillations could serve as an internal reference signal. Neuronal spike trains could then encode information in the phase of a pulse with respect to the background oscillation. If the input does not change between one cycle and the next, then the same pattern of phases repeats periodically [23].

3.3 Temporal coding

The temporal coding means that information is encoded in the precise timing of spikes emitted by neurons. This incorporates time domain within computation. It is essential to have neurons spike at desired times because this is required to achieve computations in the time domain. The spike time of the neuron is defined as the time when its membrane potential first reaches a firing threshold ([32], [33], [34]). Rate coding models suggest that these irregularities are noise, while

temporal coding models suggest that they encode information [35]. After spikes, let us now review another property of biological neural network called ‘plasticity’.

4. Adaptability (plasticity) in neural networks

Property of biological neural networks to be able to adapt to the surroundings and to enhance performance in attaining specific tasks is known as Adaptability. In order to replicate same behavior artificially with some degree of accuracy, artificial neural networks have been designed, however the whole process is not yet fully understood. The definition of learning in neural networks given by S. Haykin [36] is most suitable:

“Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place”

This definition shows that learning is a process which takes place in steps i.e.

i. Network receives stimuli from the environment
ii. Depending upon the inputs, free parameters of the network are modified
iii. New output is generated by the network corresponding to the input, where modifications occur because of the changes described in the previous step.

The second is done by what is known as ‘learning algorithm’. It means a well-defined set of rules which describe how the modifications in the network occur as a consequence of the incoming stimuli [36].

5. Plasticity in artificial neural networks

There are three parameters namely learning paradigms, learning rules and learning tasks which needs to understand in order to understand plasticity in ANN. These are being described next [36].

5.1 Learning paradigms:

There are four main paradigms which describe the learning environment in which the neural network operates:

Supervised learning*:* Learning in the presence of input set and desired output is known as supervised learning. In the presence of both inputs and desired outputs, the network is able to configure itself by reducing error in each iteration. Error reduction is achieved by modifying the parameters of the internal structure of the network [36]. Various supervised learning algorithms along with their limitations are going to be presented next.

Ponulak in [37] had stated that it is generally agreed that artificial Spiking Neural Networks (SNN) are capable of exploiting time as a resource for coding and computation in a much more sophisticated manner than typical neural computational models. SNNs appear to be an interesting tool for investigating the temporal neural coding and for exploiting its computational potential. Although significant progress has already been made to recognize information codes that can be beneficial for computation in SNN, it is still an open problem to determine efficient neural learning

mechanisms that enable implementation of these particular time-coding schemes. As per Gardner and Andre in [38], despite of the fact that, a Spiking Neural Network (SNN) represents a third generation neural network model, being a significant improvement in terms of biological realism over its predecessors, there exist relatively few learning rules for SNN's over more traditional neural network models. Kasinski and Ponulak in [37] has presented a very detailed comparative study of various supervised learning algorithms methods for spike time coding in Spiking Neural Networks (SNN). Their study is motivated by the information coding in the biological neural systems which suggest that precise timing of individual spikes may be essential for efficient computation in the brain. Ponulak in [39] has presented that the idea of learning window has been introduced first for the Hebbian learning in the context of spike-based learning rules such as Spike-Timing Dependent Plasticity (STDP) ([40], [41]). Ponulak in [39] had also stated a need for defining a new learning method for SNN which inherits the advantages of the STDP approach while enabling supervision. Another spiking neuron, called 'The Tempotron', learnt with a specific learning rule, has shown how a neuron can give a binary response to information encoded in the precise timings of the afferent spikes [42]. Tempotron's output represents information through the presence or absence of an output spike during a predefined period. The timing of the tempotron's output spikes is arbitrary and does not carry information. Because of this change in the representation of information, the output of a tempotron cannot serve as the input of another tempotron [42]. For all these methods the common goal of learning can be stated as follows: Given a sequence of the input spike trains and a sequence of the target output spikes, find a vector of the synaptic weights, such that the outputs of the learning neurons are close to desired set of output spike trains.

Methods Based on Gradient Evaluation: Learning in the traditional, artificial neural networks (ANNs) is usually performed by gradient ascent/descent techniques. However, explicit evaluation of the gradient in SNNs is infeasible due to the discontinuous-in-time nature of spiking neurons. Indirect approaches or special simplifications must be assumed to deal with this problem [37]. One of such approaches is called SpikeProp ([43], [44]). The target of SpikeProp is to learn a set of the desired firing times at the postsynaptic neurons for a given set of the input patterns. It is assumed that each neuron in a simulated network is allowed to fire only once during a single simulation cycle and the time course of the neuron's membrane potential after the firing is not considered. Thus the problem of the discontinuity of the membrane potential at the firing time is avoided here [43]. Its limitation is synaptic weights cannot be changed once the postsynaptic neuron stops firing for any input pattern. Moreover, in the SpikeProp approach only the first spike produced by a neuron is relevant and the rest of the time course of the neuron is ignored. Whenever a neuron fires a single spike, it is not allowed to fire again. The method is suitable to implement only the 'time-to-first-spike' coding scheme.

Statistical Methods: The authors proposed to derive a supervised spike-based learning algorithm starting with statistical learning criteria. Their method is based on the approach proposed by [45].

However, the author considered supervised learning for neurons operating on a discrete time scale. The fundamental hypothesis in is to assume that the instantaneous firing rate of the postsynaptic neuron is determined by a point process with the time-dependent stochastic intensity that depends nonlinearly upon the membrane potential. The firing rate is known as the escape rate [23]. The goal of the learning rule considered is to optimize the weights in order to maximize the likelihood of getting postsynaptic firing at the desired times. Its limitation is thatthe learning rule is capable to set the time of single firing at the neuron output. It is not mentioned that this method is suitable for complex spike trains having multiple spikes.

Linear Algebra Methods: Carnell and Richardson proposed to apply linear algebra to the task of spike time learning [46]. In a set of experiments the authors demonstrated that the iterative algorithm is able to approximate the target time series of spikes. The experiments were performed with the Liquid State Machine (LSM) network architecture and the Leaky-Integrate-and-Fire (LIF) neuron models [41]. Only a single neuron, considered as a network output, was subjected to learning. The approximated spike train consisted of 10 spikes (spanned within a 1 second interval). In the successful training case, an input vector was generated by 500 neurons. A good approximation of target spike train was obtained after about 600 iterations. The presented results revealed that the ability of the method to produce the desired target patterns is strongly influenced by the number and variability of spikes in input spike train. The quality of approximation is improved for the increased diversity of the spikes that populate the input to the learning neuron. This is a common conclusion for all LSM systems. It is believed that this learning rule [46] is one of few rules that support learning patterns with various spikes. One of the limitation is that the requirement of this algorithm is update weights in a batch mode. Hence it is not suitable for online learning.

Evolutionary Methods: Continuous optimization problems can be easily solved by Evolutionary Strategy [47]. This rule has both synaptic strengths and delays as adjustable parameters. The spiking network is mapped to a vector of real values, which consists of the weights and delays of synapses. A set of such vectors will form the population evolving according to the ES. The population is expected to converge to a globally optimal network, tuned to the particular input patterns. Feed forward fully connected spiking networks and SRM neuron models were used. Some limitations of the algorithm arise due to the fact that each neuron is allowed to generate at most a single spike during the simulation time. Therefore, the method is not suitable for learning patterns consisting of multiple spikes. This approach has time consuming computation.

Learning in Synfire Chains: An SFC is a feed forward multi-layered architecture, in which spiking activity can propagate in a synchronous wave of neuronal firing from one layer of the chain to the successive ones. Each step in the SFC requires a pool of neurons whose firings simultaneously raise the potential of the next pool of neurons to the firing level. In this mechanism each cell of the chain fires only once [46]. Sougne, introduced a specific neural architecture, called INFERNET.

The target was to regenerate the temporal relation between two successive inputs [48].
The first one is the input to first layer and the other one treated as the 'teaching' signal, which is fed to the last layer. Thus the task is to identify an association between the firing input nodes and the firing target nodes with a target time delay. In the reported approach, the author introduces a learning algorithm in which the particular synaptic connections are modified by a rule similar to STDP, with, however, an additional non-Hebbian term which depicts the weight changes of the synaptic connection from the neuron. The learning algorithm implies that synaptic weights between the particular neurons must become strong enough to ensure that the wave of excitation reaches eventually the output subnet. We conclude that the learning method under consideration represents an interesting approach to the spike time learning problem in SNNs. In this method, it is assumed that the time of postsynaptic neuron firing depends mostly on the signal propagation delay in pre synaptic neurons. The 'time-weight' dependence is neglected. The author focuses on modifying the topology of the network, to obtain the desired delay between the signal fed to the network input and the signal generated at the network output. One of the limitation with this approach, is that the objective function which is desired time delay is not a continuous function of the parameters which are synaptic weights of the optimization algorithm. So, the algorithm can be considered as a discrete optimization technique. This approach makes it possible to attain precision that takes values not from the continuous domain, but from a finite set of possible solutions. It has another limitation that it can learn only single firing times and thus can be applied only to the 'time-tofirst-spike' coding scheme.

Spike-Based Supervised Hebbian Learning: This approach makes use of additional 'teaching' signal in supervising Hebbian processes (Hebb, 1949). According to this approach, Hebbian processes are supervised by an additional 'teaching' signal that rewards the postsynaptic neuron to fire at the target times. The 'teaching' signal can be transmitted to the neuron in the form of synaptic currents or as intracellularly injected currents. A thorough analysis of the supervised Hebbian learning in the context of spiking neurons was performed by [49]. Because of the learning method and the teaching signals, learning neuron only fires at desired times. If we tlak about limitation then the target firing times are the only timings when pre and postsynaptic activities occur. No association occurs at other times. Thus no mechanism to change synaptic weights at other times so there are chances that neuron may fire at undesired times during testing. Another reported problem is, synapses keeps on changing their parameters even if the neuron fires already exactly at the desired times. Thus, stable solutions can be achieved only by applying some additional constraints or extra learning rules to the original supervised hebbian learning.

Remote Supervision (ReSuMe): ReSuMe, the Remote Supervised Method proposed in [50]. It is argued that the method possesses interesting properties of the supervised Hebbian approach while avoiding its drawbacks. The goal of ReSuMe learning is to impose on a neural network the desired input-output properties, i.e., to produce the desired spike trains in response to the given input sequences. ReSuMe makes use of two approaches, one is Hebbian and other is remote supervision.

The high learning ability of ReSuMe has been confirmed through extensive simulation experiments. It was presented by Ponulak that ReSuMe was used to train a network to produce the desired sequence of the spikes in response to a given, specified input spike train. ReSuMe was applied to the LSM network consisting of 800 LIF neurons. Both input and output spike trains were generated randomly over a time interval of 400 ms. A single learning neuron was trained over 100 learning sessions. It is evident that after the training, the resulting output sequence is almost identical with the target **[50]**. It is believed that ReSuMe is an efficient learning method, potentially suitable for real-life and real-time applications.

Chronotron: Recently, a method called Chronotron was proposed in [51]. It is based on minimizing the error between the desired spike pattern and the actual one. The error is measured using the Victor Purpura spike distance metric [41]. This metric produces discontinuities in the error landscape that must be overcome through approximation. E-Learning is compared with ReSuMe on some temporal classification tasks and its better performance in terms of the number of spike patterns that can be classified is shown. Memory capacity of Chronotron is also lower bound.

DL-ReSuMe:This is the latest remote supervised learning rule for spiking neurons which has been proposed by [52]. This learning rule makes use of more biologically plausible properties, such as delay learning, and needs less weight adjustment than ReSuMe. It states that the maximum number of the existing learning methods for SNNs are dependent on weight adjustment. However, there is also biological evidence that the synaptic delay is not constant. Limitation of proposed DL-ReSuMe method is it can learn input spike trains of shorter duration and smaller mean frequency with a higher accuracy and much faster learning speed than ReSuMe. In addition, low output spike train frequency increased the performance of DL-ReSuMe. It was also found that the maximum allowable synaptic delay can affect the accuracy of DL-ReSuMe.

So it is evident that there is a scope to explore existing learning rules for a SNN such that neuron of network should be able to learn associations between spatio-temporal input-output spike trains.

Unsupervised learning*:* There is no desired output set in this kind of learning. So network has to learn only through the experience collected by input training patterns [36].

Reinforcement learning*:* In this kind of learning, whenever a network generates a positive output, it is rewarded and therefore is reinforced; actions that did not produce the desired outcome are penalized. This has reward function that reinforces the correct behavior [53]. A link between the theory behind this type of learning and its biological implementation in neural networks has been found only recently [14].

***Evolutionary learning**:* Biological evolution is the process through which individuals are selected as the ones that have best adapted to the environment. This happens through adaptation to the environment on the time span of generations: life forms that have achieved a better adaptation to the environment are also able to live longer and reproduce more. Therefore, through natural selection, the "winning" genes are the most diffused across the individuals of a particular population. As evolution has been described in biology, similar processes can be also described in numerous other fields [54]. In particular it has been described in artificial neural networks through evolutionary algorithms.

5.2 Learning rules

Learning algorithms for neural networks may be based on a series of principles [53]. Detailed explanation is present in [36]. Some of them are:
Error-correction learning: The output generated by the network is compared with the desired output, and this error signal is used to make the appropriate changes to the synaptic weights. This rule is used in a supervised learning environment.

Memory based learning: All the injected inputs are compared with those previously stored in memory. The input is then attributed to the class of its closest neighbor that is present in memory.

Hebbian learning: The STDP learning rule belongs to this category.

Competitive learning: The output neurons of a network compete among themselves to become active, inhibiting the others. This rule is used later in this thesis in addition to the Hebbian learning rule described earlier.

5 Applications

Spiking neural networks (SNN) have gained popularity in embedded applications such as robotics and computer vision. The main advantages of SNN are the temporal plasticity, ease of use in neural interface circuits and reduced computation complexity. SNN have been successfully used for image classification. They provide a model for the mammalian visual cortex, image segmentation and pattern recognition. In [55] a simplified and computationally efficient model of spike response model (SRM) neuron with spike-time dependent plasticity (STDP) learning is presented. Frequency spike coding based on receptive fields is used for data representation; images are encoded by the network and processed in a similar manner as the primary layers in visual cortex. The network output can be used as a primary feature extractor for further refined recognition or as a simple object classifier. Results show that the model can successfully learn and classify black and white images with added noise at an equivalent classification ratio when compared to classic SRM neuron membrane models [55].
Based on the information processing functionalities of spiking neurons, a hierarchical spiking neural network model is proposed to simulate visual attention in [18].

The proposed spiking neural network is combined with the edge detection network model in [19]. If a visual image is presented to the edge detection network, edges of the image are reflected in the output neuron array in [19]. The spike trains from this neuron array are regarded as inputs for the proposed network in this paper. Various receptive fields and hierarchical structures of spiking neurons enable a spiking neural network to perform very complicated computation tasks, learning tasks and intelligent behaviors in the human brain. This paper proposed a spiking neural network model that can perform visual attention based on image features of horizontal and vertical lines. Simulations show that the proposed network is able to obtain attention area based on the inherent horizontal and vertical lines, for example a house. Based on this principle, other more complicated image features can also be used in this attention mechanism to focus on more complicated objects.
Spiking neural networks (SNN)-based architectures have shown great potential as a solution for realizing ultra-low power consumption using spike-based neuromorphic hardware [56]. The work in [56] describes a novel approach for converting a deep CNN into a SNN that enables mapping CNN to spike-based hardware architectures. Their approach first tailors the CNN architecture to fit the requirements of SNN, then trains the tailored CNN in the same way as one would with CNN, and finally applies the learned network weights to an SNN architecture derived from the tailored CNN. Resulting SNN was evaluated on publicly available Defense Advanced Research Projects Agency (DARPA) Neovision2 Tower and CIFAR-10 datasets and show similar object recognition accuracy as the original CNN.
Spiking Neural Network has applications in the area of neuroscience as well for example modelling of dorsal region of the raphe nucleus (DRN) [57] and modelling of hippocampal system to some extent [58]

6 Motivation

As per the comparative study of various existing spiking neuron models, it is evident that out of many spiking neurons model available, the question of which one to choose depends on the type of the problem [22]. There are limitations in those existing spiking neuron models and there is a scope to explore more. Broad category of limitations are following:

- Inability to produce maximum firing patterns of a real neuron
- Too much floating point operations
- Less quality of adaptability i.e. less capability to store information/memory of previous spike.

Apart from this, latest advancement in this area is the development of A Million-Plus Neuron Model of the Hippocampal Dentate Gyrus [58]. This shows that spiking neuron models have huge scope in modelling various regions of brain in order to explore the working to some extent.
It has become attainable goal in recent years to develop large-scale, quantitatively based models of neural systems [59].
Spiking Neural Network models use trains of spikes as internal information representation rather than continuous-value variables. Many studies investigate how to use SNN for practical applications, some of them demonstrating very promising results in solving complex real world

problems. However, due to the increased complexity of SNN compared to traditional artificial neural networks, the training of these networks in a supervised fashion has proved to be difficult [5]. Learning in neural networks that represent information through a firing rate code has been thoroughly studied [60]; however, we have lacked efficient, theory-supported learning rules for spiking neurons with temporal coding of information [51].
Spiking Neural Networks has the potential and capability to model complex information processing in the brain. However, the exact learning mechanism in which the neuron is trained to fire at precise times remains an open problem [52].

7 Objectives

A brief review about the current trends in the spiking neural networks and the involved learning laws has been discussed above and has identified wide vistas to explore.
These include:

- Research investigations into various spiking neural network systems and systematically analyze the system parameters and associated behavior.
- Explore the possibility of optimization and enhancement at any of the following levels: neuronal, signal processing and network architecture
- Researching efficient learning rules and
- Applying such systems to problems on various application domains like pattern recognition and classification.

It is proposed to limit our research in this thesis to an appropriate mixture and subset of the issues identified above.

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